INTERREGIONAL R&D SPILLOVERS IN EUROPE

Myriam ABDELMOULA [*] **and Diègo LEGROS** [**]

Abstract **-** *Our paper identifies and estimates the effects of R&D spillovers on total factor productivity with consideration of spatial effects. We first run our estimations on the Coe and Helpman (1995) model introducing spatial correlation. The results show positive R&D spillover effects on TFP and high spatial dependency among countries. We then run the same estimations on regional data. Due to a lack of information about trade between regions, we construct our trade matrix using regional transport information. We obtain a trade matrix for 57 European regions. Estimation results confirm spatial dependency and positive spillovers effects.*

Keywords**:** PRODUCTIVITY, PANEL, COINTEGRATION, SPATIAL MODEL, EUROPEAN REGIONS.

JEL Classification**:** C23, C25, J24, L60, O31.

[*] Ermes (CNRS), Université Paris II Panthéon-Assas. E-mail: myriam.a@noos.fr
[**] Corresponding author. Laboratoire d'Economie et de Gestion (LEG), Université de Bourgogne. E-mail: diego.legros@u-bourgogne.fr

1. INTRODUCTION

Innovation and productivity are interlinked. Innovation improves production processes and costs while making management tools more efficient. Knowledge diffusion is important for economic growth and enhances productivity. Knowledge can be disseminated through many channels such as international trade, foreign direct investment (FDI) and communication networks. During the 1990s, trade as a channel for knowledge diffusion was an important subject of analysis. The earliest relevant work was done by Coe and Helpman (1995). They showed that positive research and development (R&D) spillovers induced by trade increase the productivity of absorbing countries. Hence, countries can gain from the diffusion of technology and from other benefits associated with international trade. Later, Coe et al. (1997), Keller (1998 and 1999), Kao (1999), and Park (2004) used various data sets, models and methods to investigate R&D spillovers. With regard to FDI as a channel for knowledge diffusion, authors like Blomstrom and Kokko (1998) showed that FDI has a cyclic effect on a country's growth; growth is higher when the proportion of foreign firms is higher. Moreover, workers like Konings (2001) proved that FDI leads to both positive and negative R&D spillovers. Reflecting competition effects, negative spillovers can handicap the absorbing country's growth. Other commentators such as Séror and Rejeb (1996), Moen (2005) and Van Pottelsberghe (1997) studied other knowledge diffusion channels such as researchers' mobility and collaboration. Unfortunately, due to a lack of data, fewer empirical studies on R&D spillovers have been made using these channels.

As concerns trade as a knowledge diffusion channel, the impact of R&D spillovers on the total factor productivity of European regions and the exploration of the spatial distribution of regional innovative activity has still not been analysed. The aim of this study is to fill this research gap. We therefore estimate the impact of local and foreign R&D on productivity performance using the specification of Coe and Helpman (1995). They suggest that a country's productivity depends on its own R&D activities and on the R&D activities of its trading partners. We consider data for 57 European regions over the period 1995-2002. Our data is from an original panel database covering French, Spanish, Italian, German and Belgian regions. As in Kao, Chiang and Chen (1999) for Coe and Helpman data, we will show that regional processes are not stationary and we will apply the theory of asymptotic cointegration panels. However, Baltagi, Bresson and Pirotte (2007) show that unit root tests are not robust in cases of spatial dependency, so we will test for spatial correlation in our data. If the result is positive, we will estimate a new spatial model. For this reason, we will construct a regional trade matrix to study regional spillovers. Due to insufficient information about trade between regions, we construct our trade matrix using regional transport information.

The contribution of this work is twofold: we construct a regional trade matrix using regional transport information; the common matrix used for studying regional effects is geographical. Then, we study regional spillovers for

57 European regions taking into account the spatial dependency between regional units.

The remainder of the paper is organized as follows. The theoretical framework is developed in section 2. Section 3 explains the estimation strategy. Section 4 presents the data. The results of the analysis are detailed in section 5. Finally, section 6 concludes.

2. THEORETICAL FRAMEWORK

Coe and Helpman (1995) claim that the productivity of a global economy depends on its own stock of knowledge as well as the knowledge of its trade partners and they use a panel data set to study the extent to which a country's productivity level depends on its domestic and foreign stock of knowledge. They use a country's cumulative R&D spending to measure the domestic stock of knowledge, and the foreign stock of knowledge is calculated as the import-weighted sum of cumulated R&D expenditure of its trading partners. The size of the R&D capital stock is measured by the elasticity of total factor productivity with respect to the R&D capital stock. Following Coe and Helpman (1995), we regress total factor productivity on two variables: domestic and foreign R&D capital stock.

Total factor productivity (TFP) is expressed as production per unit of several inputs. Generally, two methods can be distinguished in the literature to obtain TFP: the growth accounting approach and the production function approach. Both methods produce the same results when the underlying production function is assumed to exhibit constant returns to scale and when both product and factor markets are competitive. TFP growth then corresponds to the neo-classical concept of technical change. The TFP growth estimates in this paper are constructed by the growth accounting approach using input-output data. The total factor productivity (TFP) is constructed as in Coe and Helpman (1995).

Consider the popular and convenient Cobb-Douglas functional form:

$$Y = AK^{\alpha}L^{\beta} \tag{1}$$

Constant returns to scale induce $\alpha + \beta = 1$. Hence, TFP is obtained by the formula:

$$TFP = \frac{Y}{K^{\alpha}L^{1-\alpha}} \tag{2}$$

where Y is the value-added, K is the stock of capital, and L is employment. β is the average share of capital income. Golin (2002) shows that 1/3 and 2/3 are correct estimations for the share of capital and the share of employment given that the share of employment in developed countries lies between 0.65 and 0.85.

Accordingly we construct the logarithm of TFP as:

$$\log TFP_{it} = \log Y_{it} - \frac{1}{3}\log K_{it} - \frac{2}{3}\log L_{it}$$

Y_{it} is the gross domestic product (GDP) of region i at date t. L_{it} is the employment level and K_{it} is the capital stock.

The capital stock K_{it} is constructed on the basis of the perpetual inventory method:

$$K_{it} = (1-\delta)\, K_{it-1} + I_{it-1} \quad (3)$$

$$K_{i0} = \frac{I_{i0}}{\gamma_i + \delta}$$

where I_{it} is the investment in the physical capital of region i at date t; δ is the depreciation rate of the capital and γ_i the average annual logarithmic growth of capital investment over the period 1995-2002. According to recent literature[1], we use $\delta = 7\%$[2]. As we have no information about regional investment in physical capital, we approximate it from the total gross fixed capital formation.

3. DATA AND DESCRIPTIVE STATISTICS

As noted for instance by Puga (1999), there are larger income disparities across European regions than among US States but we need to work on this. We use data from REGIO, a Eurostat data base, to estimate the determinants of total factor productivity. REGIO relates to European NUTS (Nomenclature des Unités Territoriales Statistiques) regions and contains several missing values. We tried to construct homogeneous regions depending on the availability of data. We employed NUTS1 level for Belgium (e.g. Bruxelles-capitale and Vlaams Gewest) and Germany (e.g. Bayern and Baden-Württemberg) and NUTS2 level for France (e.g. Ile de France and Alsace), Italy (e.g. Lombardia and Toscana) and Spain (e.g. Comunidad Valenciana and Andalucìa). Variables relate to 57 regions over the period 1995–2002. The distribution of regions by countries is Belgium 3, Germany 11, Spain 14, France 21 and Italy 8. The list of regions is appended.

We constructed import flows of goods m_{ij} by using data on the transport of goods from one region to another. As the trade structure is considered constant over the period 1995-2002, we constructed E for the year 2000. Data were collected from several institutions: Institut National de Statistique (Belgium), Banque Nationale de Belgique, Institut des Comptes Nationaux (Belgium), Service Public Fédéral Mobilité et Transport (Belgium), Douane

[1] Fraumeni (1997), Whelan (2002) and Oulton and Srinivasan (2003) present a discussion on recent estimations of the depreciation rate of capital.

[2] We ran the same estimations with $\delta = 0.05$ and $\delta = 0.10$. The results do not change significantly.

Française (France), Ministère des transports, de l'équipement, du tourisme et de la mer, Directions régionales de l'équipement (France), Instituto Nacional de Estadistica (Spain), Ministerio de Fomento (Spain), Institut Valencia d'Estadistica (Spain), Confetra (Italy), Ministero delle Infrastrutture e dei Trasporti (Italy), Instituto Nazionale di Statistica (Italy), Statistisches Bundesamt (Germany) and Kraftfarht Bundesamt (Germany). We constructed the matrix *E* for all 57 European regions.

All variables are constructed in indices using 1998 as the reference year. R&D domestic capital stocks ($S^{d,}$) as a proxy for knowledge capital stocks are constructed by the perpetual inventory method (Razzak and Margaritis, 2002):

$$S^{d,t} = (1-\alpha)S^{d,t-1} + R\&D_{t-1} \quad (4)$$

$$S_0^d = \frac{R\&D_0}{\alpha + g} \quad (5)$$

where α is the depreciation rate (assumed to be 10%[3]), $R\&D_{it-1}$ the R&D investment of region *i* at time *t-1* and *g* the average annual logarithmic growth of R&D expenditure over the period 1995-2002. R&D expenditure is R&D investment in millions of purchasing power standard at 1995 prices.

Foreign R&D capital stocks ($S^{f,}$) are constructed as in Coe and Helpman (1995). It is the import share weighted average of the domestic R&D capital stocks of trade partners:

$$S_i^f = E.S_j^d \quad (6)$$

where *E* is the weight matrix defined as:

$$E = \sum_{i \neq j} \frac{m_{ij}}{m_i} \quad (7)$$

where m_{ij} is the flow of imports of goods of region *i* from region *j*, m_i is the flow of imports of goods of region *i* from its 56 trade partners (i.e. $m_i = \sum_j m_{ij}$) and S_j^d is the R&D capital stock of other regions ($i \neq j$). This construction of foreign R&D capital stock assumes that the more open a region is to high R&D capital stock producers, the greater its foreign R&D stock.

Table 2 gives some descriptive statistics. TFP increases between 1995 and 2002 in all Belgian, French, German and Spanish regions. Five out of the eight Italian regions considered have a TFP that decreases over the period. The highest growth rates are found in German regions: Thüringen (35%),

[3] We ran the same estimations with 5% and 15% depreciation rates and obtained similar results.

Mecklenburg-Vorpommern (Dusseldorf) (32.7%), Sachsen (Dresden) (32.5%) and Bayern (Munich) (25%). In the other countries, the leading regions are Provence-Alpes-Côte d'Azur (Marseille) for France with an 18% increase in TFP, Andalousia (Seville) is the leading Spanish region with 11.3%, the Belgian region of Bruxelles-Capitale with 17.5% and the Italian region of Lazio (Rome) with only 2.2%. On average, TFP increases by 12.17% over the period 1995-2002. Except for Bourgogne (Dijon) (10.8%), all other French, German and Belgian regions have higher than average growth rates. All Spanish and Italian regions have growth rates of less than 12.17%.

R&D domestic stocks increase in all regions except for Bruxelles-Capitale (-7%). This growth averages 16.79%. The French region of Auvergne (Clermont-Ferrand) has the highest growth rate (44.6%), followed by the Spanish region of la Rioja (Logrõno) (40.7%) and the French region of Champagne-Ardenne (Chalons-en-Champagne) (36%). In the other countries, R&D capital stock increased greatly in the Belgian region of Flandre (Anvers) (30.2%), the German region of Hannover (20.7%) and the Italian region of Bologna (14.2%). The lowest growth rates are in Cantabria (Santander) (0.3%) in Spain and in the Italian regions of Piemonte (Turin) (2.6%) and Veneto (Venezia) (3%).

Foreign R&D stock increases by 11.34% on average. Italian and Spanish regions record the highest growth rates: Spanish regions are Aragon (Zaragoza) (18.7%), Murcia (18.3%) and Cantabria (Santander) (17.8%), closely followed by the Italian region of Veneto (17.8%). German and French regions are very close together at the bottom of the ranking, especially with the regions of Basse-Normandie (Caen) (5.8%), Schleswig Holstein (Kiel) (5.9%), Niedersachsen (Hannover) (6%) and Picardie (Amiens) (6.6%). In Belgium, all regions have almost the same foreign R&D growth rates (around 8.8%).

4. ECONOMETRIC METHODS

Like Coe and Helpman (1995) we analyse the reduced form of a long term equilibrium relationship, so it is natural to try to find a cointegration representation (Edmond, 2001). Several studies have examined whether the time series behavior of economic variables is consistent with a unit root (for a survey, see Diebold and Nerlove, 1988; Campbell and Perron, 1991). Starting from the seminal works of Quah (1990, 1994), Breitung and Meyer (1991) and Levin and Lin (1992), many tests have been proposed attempting to introduce unit root tests in panel data. They show that combining the time series information with that from the cross-section, the inference about the existence of unit roots can be made more straightforward and precise, especially when the time series dimension of the data is not very long and similar data may be obtained across a cross-section of units such as countries or industries. A second advantage when using panel unit root tests is that, whereas many of the estimators and statistics for unit root processes in time series are complicated distributions of Wiener processes, the former estimators are normally distributed. This result is still robust when heterogeneity is introduced across the units comprising the panel. However Baltagi, Bresson and Pirotte (2007) show that stationarity tests are not robust in cases of spatial dependence. Our estimation strategy is therefore first to use panel cointegration techniques and then to use spatial econometric methods.

4.1. Panel cointegration estimation

One difficulty that can arise when regressing two non-stationary series is the problem of spurious regression: when using two unrelated integrated series, regressing one on the other tends to produce an inconsistent but apparently significant structural coefficient, Granger and Newbold (1974). By contrast with the pure time series spurious regression, in the case of non-stationary panel data, Phillips and Moon (1999) show that for the spurious panel regression, and under quite weak regularity conditions, the pooled least squares estimator of the structural coefficient is consistent and has a limiting normal distribution. The reason is that independent cross-section data in the panels introduce information and this leads to a stronger signal than in the pure time series case. The problem here is that while the structural parameters linking the variables converge to the true values, their *t*-statistics diverge, so inferences are wrong with probability that goes to one asymptotically, Kao et al. (1999). In the empirical analysis we will use two sets of cointegration tests. The first set of tests has been proposed by Kao et al. (1999), and can be seen as a generalization of the Dickey-Fuller (DF) and Augmented Dickey-Fuller (ADF) tests in the context of panel data. The second set of tests used has been proposed by Pedroni (1999, 2004). All the tests consist of taking the hypothesis of no cointegration as null and using the residuals derived from a panel static regression to construct the test statistics and tabulate the distributions. After appropriate standardization, all tests have asymptotic distributions that converge to a standard normal distribution.

In the case of cointegration, even if the OLS estimations are superconsistent, their distribution is asymptotically biased and depends on nuisance parameters associated with the serial correlation structure of the data.

Before making estimations, we have to check the stationarity of our data. Unit root test results are reported in Table 4. All tests show that variables $\ln S^d$, and $\ln S^f$, are integrated of order 1. Variable ln*TFP* has no unit root. So before looking at results of OLS estimations, it is necessary to run unit root tests on residuals, i.e. cointegration tests. Results are reported in Table 5. All statistics are significant: the null hypothesis of no cointegration is strongly rejected. Accordingly, other methods more suitable than OLS need to be used. As in Kao and Chiang (1999), we estimate the model by Fully Modified (FM) and Dynamic Ordinary Least Squares (DOLS).

We consider the model on which we regress the total factor productivity on two variables: domestic and foreign R&D capital stock:

$$\ln TFP_{it} = \alpha_i + \beta_1 \ln S^{d,it} + \beta_2 \ln S^{f,it} + \varepsilon_{it} \quad (8)$$

4.2. Panel spatial estimation

Since the regions of our sample are not closed economies and have a number of interactions with each other, we expect a strong spatial correlation between our data. Spatial econometrics has mainly been used to study levels of income and growth between regions. Numerous analyses (Le Gallo and Ertur, (2003) for example) show a spatial dependence between European regions. Paci and Pigliaru (2001) found when estimating spatial lag that productivity growth of an EU region is correlated with that of its neighbouring regions. Paci and Usai (2000) detect R&D spillovers between adjacent Italian regions. Funke and Neibuhr (2000) investigate R&D spillovers with spatial interaction models for West German regions and find a significant contribution of R&D spillovers to productivity growth which decays fairly rapidly with distance. Bottazi and Peri (2003) examine EU regions and similarly find that local clustering, i.e spillovers, is important for R&D results, while R&D spillovers quickly fade with distance.

So we augment equation (8) by allowing for spatial interactions through spatially lagged endogenous and/or exogenous variables. In this way, by including a spatially lagged dependent variable, we consider that labour productivity of a given region could be affected by labour productivity of the surrounding regions owing to spatial interactions. Furthermore, the introduction of spatially lagged control variables implies that the values of observations in nearby regions can also exert an influence on labour productivity in the reference region.

The starting point is the classical fixed effect panel data model (Elhorst, 2003), in which spatial dependence is accounted for by including a spatially lagged term of the dependent variable so that the model assumes the following notation:

$$\ln y_{it} = \alpha_i + \rho W \ln y_{it} + \beta \ln x_{it} + \varepsilon_{it} \tag{9}$$

with W the classical weight matrix, ρ is the so-called spatial-autoregressive coefficient, and ε_{it} is the classical zero mean error term assumed to be independent of the probability model under the hypothesis that all spatial dependence effects are captured by the spatially lagged variable term. This model takes the name of fixed effect spatial lag model. The standard estimation method for the fixed effect model is to eliminate the intercept term from the regression equation by taking the variables in deviation of their average in time, and then using OLS. In the presence of spatial autocorrelation it is common practice in spatial econometric literature (Elhorst, 2003) to use the maximum likelihood procedure to estimate the demeaned equation. The only difference is that ML estimators do not correct for the degrees of freedom. If the estimated value of the ρ parameter is significantly positive (negative), we are in the presence of positive (negative) spatial autocorrelation. An alternative way to incorporate the spatial effects is to leave the systematic component unchanged and to model the error term, for instance assuming that:

$$\ln y_{it} = \alpha_i + \beta \ln x_{it} + \varepsilon_{it}$$
$$\varepsilon_{it} = \delta W \varepsilon_{it} + \eta_i$$

where W is again the spatial weight matrix, δ is the spatial autocorrelation coefficient, and the η_i are assumed to be normally distributed with zero mean, known variance and independent from the explanatory variable. Such a model is termed a fixed effect spatial error model. Again the parameters may be estimated by using maximum likelihood. Moreover, similar consideration can be made over the estimated value of the δ parameter.

The spatial econometric literature has shown that OLS estimation in models with spatial effects is inappropriate. In the case of spatial error autocorrelation, the OLS estimator of the response parameters, while unbiased, loses its property of efficiency. In the case of a spatially lagged dependent variable, the OLS estimator of the response parameters not only loses its property of unbiasedness but also its consistency. The latter might be thought of as the minimum requirement for a useful estimator. The most commonly suggested method to overcome these problems is to estimate the model by maximum likelihood (Anselin, 1988; Anselin and Hudak, 1992). For this reason, Elhorst (2003) deals with maximum likelihood estimations.

The standard method of estimating the fixed effects model is to eliminate the intercept and μ_i from the regression equation by demeaning the y and x variables[4].

In order to study the impact of local and foreign R&D stocks on TFP, we need to choose a spatial weight matrix that illustrates the spatial correlation between regions. We think that the bilateral trade matrix E is more suitable than a geographical one. The bilateral matrix is a dissimilarity matrix. In order to identify the spatial dependence model we use Lagrange multiplier tests (Anselin and Florax, 1995). Results are given in Table 7. Because robust LM_{LAG} is higher than robust LM_{ERR} we estimate a SAR model. Table 8 shows the results of our estimation using four different specifications. The first specification is a spatial autoregressive regressive model without spatial fixed effects (SAR). The second is a SAR model with spatial fixed effects (SAR-EFS). The third is a SAR model with temporal effects (SAR-EFT) and the fourth is a model with spatial and temporal fixed effects (SAR-EFST). We use maximum likelihood for estimating these specifications.

[4] Each variable for every spatial unit is taken as the deviation of its average over time: $y_{it} - \overline{Y}_{i.}$ with $\overline{Y}_{i.} = \frac{1}{T}\sum_{t=1} Ty_{it}$, $i = 1,\dots,N$; and the same for x variables.

5. RESULTS

Panel cointegration estimation results are reported in Table 6. In all estimations, the elasticities of foreign R&D stocks with respect to the TFP are positive and significant. FM estimators are positive and significant, their intensity is lower than for OLS. In both estimations, the impact of foreign R&D is greater than that of local R&D stocks. The adjusted R^2 is weak (0.36). DOLS estimations are different from others. In the DOLS estimation, the elasticity of local R&D stock is not significant.

Kao and Chiang (1998) show that with cointegration, MCO estimators are biased and FM ones are no better. The DOLS estimation is therefore the best one. In our case, the results of DOLS estimations are fanciful: the elasticity of local R&D is not significant and that of foreign R&D is about 62%; the adjusted R^2 falls to 0.26. Following Baltagi et al. (2007), these results can be explained by spatial dependence. Accordingly we estimate our model by the spatial econometric method.

Panel spatial results are reported in Table 8. Coefficients vary with the estimation procedure. Spatial coefficient ρ is significant in all specifications. Its range is [0.59 ;0.70]. This result shows that productivity of an EU region is highly correlated with that of its neighbouring regions when estimating spatial lag models. This confirms results mentioned above (Le Gallo et al., 2003; Paci and Pigliaru, 2001; Paci and Usai, 2000; Funke and Neibuhr, 2000; Bottazi and Peri, 1999). Local and foreign R&D elasticities are positive and significant. However the level of elasticity depends on fixed effects. The spatial fixed effect model has the second best fit of all examined models and the results are consistent with the original conclusions of Coe and Helpman (1995).

6. CONCLUSION

The aim of this paper is to estimate whether domestic and foreign R&D spending affects a country's total factor productivity. We estimate the productivity of broad set of EU NUTS 2 level regions over the period 1995-2002. Spatial correlation tests reveal a spatial dependency among European regions. Estimation of a SAR model shows that substantial spatial effects exist among regions: the TFP of one region has an important impact on its neighbours' TFP. Moreover, local R&D effects on TFP are greater than R&D spillover effects. Our conclusions are interesting but fragile. In fact, many commentators have reservations about the use of TFP as a proxy for technological progress. Their misgivings relate to the method of TFP measurement, which is based on several strong hypotheses: pure and perfect competition and the absence of returns to scale. If those hypotheses are not checked, as is the case in reality, the use of a Solow residual as a proxy for technological progress will no longer be appropriate. To make the conclusion of this work more robust, it might be interesting to run this study using another proxy for technological progress: patents. That is the subject of our future work.

7. APPENDIX

7.1. Included regions

Table 1 : 57 regions			
Country	NUTS Code	Region	Capital
Belgium	be1	Region Flammande	Anvers
Belgium	be2	Region Flammande	Anvers
Belgium	be3	Region Wallonne	Namur
Germany	de1	Baden Würtenberg	Stuttgart
Germany	de2	Bayern	München
Germany	de3	Berlin	Berlin
Germany	de7	Hessen	Wiesbaden
Germany	de8	Mecklenburg-Vorpommern	Schwerin
Germany	de9	Niedersachsen	Hannover
Germany	dea	NORDRHEIN-WESTFALEN	Düsseldorf
Germany	deb	Rheinland-Pfalz	Mainz
Germany	ded	SACHSEN	Dresden
Germany	def0	Schleswig-Holstein	Kiel
Germany	deg0	Thüringen	Erfurt
Spain	es11	Galicia	Santiago de Compostela
Spain	es12	Principado de Asturias	Oviedo
Spain	es13	Cantabria	Santander
Spain	es21	Pais Vasco	Vitoria-Gasteiz
Spain	es22	Comunidad Foral de Navarra	Pamplona
Spain	es23	La Rioja	Logroño
Spain	es24	Aragón	Zaragoza
Spain	es30	Comunidad de Madrid	Madrid
Spain	es41	Castilla y León	Valladolid
Spain	es42	Castilla-la Mancha	Toledo
Spain	es51	Cataluña	Barcelona
Spain	es52	Comunidad Valenciana	Valencia
Spain	es61	Andalucia	Sevilla
Spain	es62	Región de Murcia	Murcia
France	fr10	Île de France	Paris
France	fr21	Champagne-Ardenne	Châlons-en-Champagne
France	fr22	Picardie	Amiens
France	fr23	Haute-Normandie	Rouen
France	fr24	Centre	Orléans
France	fr25	Basse-Normandie	Caen
France	fr26	Bourgogne	Dijon
France	fr30	Nord - Pas-de-Calais	Lille
France	fr41	Lorraine	Metz
France	fr42	Alsace	Strasbourg
France	fr43	Franche-Comté	Besançon
France	fr51	Pays de la Loire	Nantes
France	fr52	Bretagne	Rennes
France	fr53	Poitou-Charentes	Poitiers
France	fr61	Aquitaine	Bordeaux
France	fr62	Midi-Pyrénées	Toulouse
France	fr63	Limousin	Limoges
France	fr71	Rhône-Alpes	Lyon
France	fr72	Auvergne	Clermont-Ferrand
France	fr81	Languedoc-Roussillon	Montpellier
France	fr82	Provence-Alpes-Côte d'Azur	Marseille
Italy	itc1	Piemonte	Torino
Italy	itc4	Lombardia	Milano
Italy	itd3	Veneto	Venzia
Italy	itd4	Friuli-Venezia Giulia	Trieste
Italy	itd5	Emilia-Romagna	Bologna
Italy	ite1	Toscana	Firenze
Italy	ite4	Lazio	Roma

7.2. Descriptive statistics

Table 2 : Evolution of TFP, local R&D and foreign R&D between 1995 and 2002

Country	Regions	Δ TFP	Δ foreign RD	Δ local RD
Belgium	Region de Bruxelles-Capitale	1.1757	0.9423	1.0975
Belgium	Region Flammande	1.1534	1.3021	1.0790
Belgium	Region Wallonne	1.1299	1.1525	1.0894
Germany	Baden Würtenberg	1.1945	1.0870	1.0925
Germany	Bayern	1.2506	1.0907	1.0927
Germany	Berlin	1.1261	1.1050	1.0933
Germany	Hessen	1.1840	1.0890	1.0934
Germany	Mecklenburg-Vorpommern	1.3277	1.1290	1.0977
Germany	Niedersachsen	1.1644	1.2072	1.0601
Germany	Nordhhein-Westfalen	1.1404	1.0637	1.1201
Germany	Rheinland-Pfalz	1.1639	1.0918	1.0887
Germany	Sachsen	1.3250	1.1760	1.0903
Germany	Schleswig-Holstein	1.1942	1.0525	1.0593
Germany	Thüringen	1.3507	1.1854	1.1055
Spain	Galicia	1.0475	1.3052	1.1140
Spain	Principado de Asturias	1.0577	1.2339	1.1394
Spain	Cantabria	1.1108	1.0034	1.1786
Spain	Pais Vasco	1.1116	1.1555	1.1435
Spain	Comunidad Foral de Navarra	1.0636	1.3118	1.1565
Spain	La Rioja	1.0874	1.4077	1.1771
Spain	Aragón	1.0395	1.1374	1.1873
Spain	Comunidad de Madrid	1.1123	1.1406	1.1395
Spain	Castilla y León	1.0452	1.3229	1.1550
Spain	Castilla-la Mancha	1.0918	1.0834	1.1650
Spain	Cataluña	1.0940	1.2077	1.1254
Spain	Comunidad Valenciana	1.1113	1.3475	1.1479
Spain	Andalucia	1.1135	1.1306	1.1588
Spain	Región de Murcia	1.1130	1.2882	1.1832
France	Ìle de France	1.1522	1.0590	1.0922
France	Champagne-Ardenne	1.1411	1.3635	1.0957
France	Picardie	1.1258	1.2958	1.0665
France	Haute-Normandie	1.1455	1.0755	1.0690
France	Centre	1.1316	1.1590	1.0807
France	Basse-Normandie	1.1369	1.2433	1.0582
France	Bourgogne	1.1086	1.1365	1.0740
France	Nord-Pas-de-Calais	1.1368	1.2602	1.0680
France	Lorraine	1.1280	1.1933	1.1008
France	Alsace	1.1225	1.2203	1.0769
France	Franche-Comté	1.1568	1.0753	1.1190
France	Pays de la Loire	1.1687	1.2473	1.0941
France	Bretagne	1.1464	1.1954	1.0792
France	Poitou-Charentes	1.1654	1.2609	1.0844
France	Aquitaine	1.1644	1.1793	1.0939
France	Midi-Pyrénées	1.1433	1.1333	1.0666
France	Limousin	1.1509	1.2479	1.1044
France	Rhône-Alpes	1.1626	1.1701	1.0724
France	Auvergne	1.1339	1.4466	1.0990
France	Languedoc-Roussillon	1.1607	1.2967	1.1557
France	Provence-Alpes-Côte d'Azur	1.1830	1.0723	1.0666
Italy	Piemonte	0.9343	1.0266	1.1357
Italy	Liguria	0.9424	1.0318	1.1522
Italy	Lombardia	1.0057	1.0394	1.1428
Italy	Veneto	0.9779	1.0528	1.1784
Italy	Friuli-Venezia Giulia	0.9346	1.0394	1.1644
Italy	Emilia-Romagna	0.9661	1.1422	1.1683
Italy	Toscana	1.0084	1.0994	1.1245
Italy	Lazio	1.0218	1.0590	1.1470

Table 3: Evolution of TFP, local R&D and foreign R&D per country between 1995 and 2002

Country	Δ PTF			Δ R&D			Δ Foreign R&D		
	min	mean	max	Min	mean	max	min	mean	max
Germany	1.126	1.220	1.351	1.053	1.116	1.207	1.059	1.090	1.120
Belgium	1.130	1.153	1.176	0.942	1.132	1.302	1.079	1.088	1.098
Spain	1.040	1.085	1.114	1.003	1.219	1.408	1.114	1.155	1.187
France	1.109	1.146	1.183	1.059	1.206	1.447	1.058	1.086	1.156
Italy	0.934	0.973	1.022	1.027	1.061	1.142	1.125	1.151	1.178
All countries	0.934	1.121	1.351	0.942	1.167	1.447	1.058	1.113	1.187

7.3 Results

Table 4: Unit root test results

	log*TFP*	log*S*	log*Sf*'
Model without fixed effect			
Levin et Lin (1993)	-18.82 (0.000)	23.16 (0.999)	55.46 (0.999)
Fixed effect model			
Levin and Lin (1993)	-18.54 (0.000)	22.98 (0.999)	55.29 (0.999)
Im, Pesaran and Shin (2003)	-8.26 (0.000)	28.97 (0.999)	47.13 (0.999)
Madala and Wu (1999)	235.98 (0.000)	26.80 (0.999)	4.69 (0.999)
Individual fixed effect and trend model			
Levin et Lin (1993)	-17.81 (0.000)	23.09 (0.999)	55.25 (0.999)

Table 5: Co-integration test results

	Kao (1997)					Pedroni (1995)	
	DF_ρ	DF_t	$DF^{*,\rho}$	$DF^{*,t}$	*ADF*	*PC*1	*PC*2
Statistics	2.33	.334	3.91	4.09	4.71	24.76	23.16
P-value	0.009	0.000	0.000	0.000	0.000	0.000	0.000

Table 6: LSDV, FM and DOLS results

	LSDV	FM	DOLS
log*S*	0.3006***	0.1434***	0.0633
log*Sf*'	0.3516***	0.2741***	0.6233***
Adj R^2	0.4334	0.3632	0.2887

*** *significant at 1%,* ** *significant at 5%,* * *significant at 10%*

Table 7: Lagrange multiplier tests

Tests	Statistic	p-value
LM_{LAG}	1069.40	0.0000
R-LM_{LAG}	40.35	0.0000
LM_{ERR}	1034.10	0.0000
R-LM_{ERR}	5.07	0.0243

Table 8: SAR results

	SAR	SAR-EFS	SAR-EFT	SAR-EFST
Intercept	-0.0081***	-	-	-
log*S*	0.0914***	0.1139***	0.0851***	0.1007***
log*Sf'*	0.1663***	0.0946**	0.1545***	0.0758**
ρ	0.5929***	0.6469***	0.6399***	0.7069***
σ^2	0.0005	0.0003	0.0005	0.0003
R^2	0.7763	0.8455	0.7767	0.85234

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EFFETS DE DÉBORDEMENT DE R&D EN EUROPE

Résumé - *Notre article identifie et estime les effets de débordement de R&D sur la productivité totale des facteurs (PTF) en prenant en compte les facteurs spatiaux. Premièrement, nous effectuons nos estimations sur la base du modèle de Coe et Helpman (1995) dans lequel nous introduisons de la corrélation spatiale. Les résultats indiquent la présence d'effets de débordement de R&D sur la PTF et une forte dépendance spatiale entre pays. Deuxièmement, nous effectuons les mêmes estimations sur données régionales. En l'absence d'information sur le commerce entre régions, nous construisons une matrice de commerce en utilisant l'information sur le transport régional. Nous obtenons une matrice de commerce pour 57 régions européennes. Les résultats confirment la présence de dépendance spatiale et d'effets de débordement positifs.*